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Stochastic Effects of Renewable Energy and Loads on Optimizing Microgrid Market Benefits

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Abstract

This paper investigates the effects of uncertain renewable energy and loads on optimizing profit and cost in a microgrid power market. The optimal power scheduling problem is solved using interval arithmetic backward forward sweep (IA-BFS) and particle swarm optimization with time varying acceleration coefficients (PSO-TVAC) based optimal power flow (OPF). The effectiveness of the problem and the method is verified by studying the deviations in dispatch of conventional sources, operational cost and overall profit in residential feeder of the CIGRE LV benchmark microgrid with load curtailment, grid trade and wind, solar & conventional energy sources.

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*Keywords:*Microgrid, Market, PSO, Stochastic, OPF, Wind, Solar

1. Introduction

A microgrid is a group of inter-connected loads and distributed energy resources (DERs) that act as a controllable entity with respect to the grid and that connects and disconnects from the grid to operate in grid-connected and islanded modes [1].Energy management in a microgrid is solved using optimization methods like priority listing [2], genetic algorithms [3], PSO [4] etc.considering renewable energy and demand as deterministic.But in practice, the energy management and scheduling problems should consider the uncertain nodal power injections (+ve or -ve) from the aforementioned sources for effective operational planning.

A percentage of choices which help the engineers and policy makers to broaden the commercialization in a microgrid are demand response [5], [6], grid trade [7], liberalization of the market [8] and PHEVs [9]. Separate prioritization of critical and non-critical loads for curtailment [10], maximum utilization of cheaper grid power at

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Nomenclature

n, m	Number of conventional and renewable generators in the system
C	Open market price
$\mathrm{Exp(P)}$	Expenses of the MGCC
$\mathrm{Rev(P)}$	Revenue of the MGCC
$\mathrm{Profit(P)}$	Overall profit of MGCC
$\mathrm{P_{gi}}$	Active-power generated (kW) from the $\mathrm{i^{th}}$ DER
$\mathrm{P_d}$	Instantaneous active-power demand (kW)
$\mathrm{P_{gi}^{(min)}}$&$\mathrm{P_{gi}^{(max)}}$	Lower and upper bounds of active power generation (kW) of DERs respectively
$\mathrm{P_{grid}}$	Power purchased/ sell from/ to the grid
$\mathrm{P_{grid}^{(max)}}$	Max power that can be traded with the grid
$\mathrm{Gbid}\left(\mathrm{P_{gi}}\right)$	The bid of the i^{th} DER
$\mathrm{P_j}$	The active power curtailed from j^{th} consumer
$\mathrm{P_j^{(max)}}$	Maximum curtailable load for j^{th} consumer
$\mathrm{lbid(P_j)}$	The j^{th} consumer bid
l	The total number of consumers who have submitted their bids for curtailable load option
$\mathrm{b_{i,conv}}$	The sum of fuel cost and emission cost in \$/kWhfor conventional generators
$\mathrm{b_{i,ren}}$	Annual depreciation for kWh output for renewable energy sources
$\mathrm{c_i}$	The expected hourly profit
β_j	Percentage of market price given as compensation for the j^{th} consumer for load curtailment
$\mathrm{P_d}$	Interval of demand due to uncertainty
$\overline{\mathrm{P}}_\mathrm{d}$	Upper bound of demand interval
$\underline{\mathrm{P}}_\mathrm{d}$	Lower bound of demand interval
$\mathrm{P_{d0}}$	Midpoint/central value of demand interval
$\varepsilon_{\mathrm{d,pos}}$	Maximum percentage of uncertainty of the forecasted demand in the positive direction
$\varepsilon_{\mathrm{d,neg}}$	Maximum percentage of uncertainty of the forecasted demand in the negative direction
$\mathrm{P_{gw}}$	Interval of wind generation due to uncertainty
$\mathrm{P_{gs}}$	Interval of solar generation due to uncertainty
$\overline{\mathrm{P}}_\mathrm{gw}$	Upper bound of wind generation interval
$\underline{\mathrm{P}}_\mathrm{gw}$	Lower bound of wind generation interval
$\overline{\mathrm{P}}_\mathrm{gs}$	Upper bound of solar generation interval
$\underline{\mathrm{P}}_\mathrm{gs}$	Lower bound of solar generation interval
$\mathrm{P_{gw0}}$	Midpoint/central value of wind generation interval
$\mathrm{P_{gs0}}$	Midpoint/central value of solar generation interval
$\varepsilon_{\mathrm{w,pos}}$	Maximum percentage of uncertainty of the forecasted wind generation in the positive direction
$\varepsilon_{\mathrm{w,neg}}$	Maximum percentage of uncertainty of the forecasted wind generation in the negative direction
$\varepsilon_{\mathrm{s,neg}}$	Maximum percentage of uncertainty of the forecasted solar generation in the negative direction
$\varepsilon_{\mathrm{s,pos}}$	Maximum percentage of uncertainty of the forecasted solar generation in the positive direction
$\mathrm{x_{i,d}}^{\mathrm{ic}}$	$\mathrm{i^{th}}$ element of $\mathrm{d^{th}}$ particle in $\mathrm{ic^{th}}$ iteration
$\mathrm{v_{i,d}}^{\mathrm{ic}}$	Velocity of $\mathrm{i^{th}}$ element of $\mathrm{d^{th}}$ particle in $\mathrm{ic^{th}}$ iteration
ω^{ic}	Inertia factor in $\mathrm{ic^{th}}$ iteration
$\mathrm{rand_1, rand_2}$	Random numbers generated between 0 and 1
$\mathrm{a_1, a_2}$	Cognitive and social parameters to control the behavior and efficacy of the PSO method
$\mathrm{ic_{max}}$	Maximum number of iterations for PSO

off-peak hours [11], and encouragement of low cost and emission-less DERs in the markets [12] should be endorsed to make the energy and cost management more effective. However, for a microgrid that participates in market, the target revenue of operator and DER owners, node voltages and power flow could be perturbed by the unpredictable nature of renewable energy, load and other stochastic aspects. It is not easy to analyze these effects. Moreover, technical constraints should also be fulfilled for a practical dispatch. Hence, method of power flow also put an essential part in incorporating uncertainties in nodal power injections corresponding to the uncertain energy sources.

In this paper, an optimal power scheduling problem which simultaneously targets on both economic and network benefits of a liberalized microgrid market model considering percentage uncertainties in wind & solar generation and loads is formulated and solved by PSO-TVAC and IA-BFS based OPF. Fuel and emission costs of DERs, expected hourly profits, compensation for load curtailment and cost/revenue of buying/selling of power from/to the main grid are the factors which decide the economic benefits of the operator. The formulated problem and the proposed method is implemented in the CIGRE LV benchmark microgrid [13], comparing the effects of uncertainties on two different market objectives of the operator viz. 1) overall profit maximization and 2) operational cost minimization.

The remainder of the paper is organized as follows. Problem formulation and constraints are explained in Section 2. The methodology of IA-BFS and PSO-TVAC based OPF is given in Section 3. The microgrid system and its specifications are given in Section 4. Results and discussions of the stochastic effects on the two policies adopted by the microgrid operator are discussed in Section 5. The paper is concluded with the summary of key points in Section 6.

2. Problem Formulation

In this paper, the microgrid is considered as a liberalized/free market model in which DER and load bids are submitted to the operator for finalizing the power schedule on hourly basis. The microgrid central controller (under the operator) sends this optimal schedule to the local controllers for implementation. Fuel cost, emission cost and expected hourly profit are incorporated in the DER bids. The amount of demand which can be curtailed and the compensation expected, are contained in the load bid.MGCC gets it'sRev(P) by selling the power that is purchased from the grid (P_{grid}) and DERs ($\sum_{i=1}^{m+n} P_{gi}$) to the consumers at the open market price (C). Expenses (Exp(P)) for the MGCC are the compensation for load curtailment ($\sum_{j=1}^{l} \mathrm{lbid}(P_j)$), price of grid power purchase $\left(C \times P_{grid}\right)$ and power purchase from DERs ($\sum_{i=1}^{m+n} \mathrm{Gbid}\left(P_{gi}\right)$).

$$Rev(P) = \left(C \times P_{grid}\right) + \left(C \times \sum_{i=1}^{m+n} P_{gi}\right) \tag{1}$$

$$Exp(P) = \left[\sum_{i=1}^{m+n} Gbid\left(P_{gi}\right) + \left(C \times P_{grid}\right) + \sum_{j=1}^{l} lbid\left(P_j\right)\right] \tag{2}$$

$$bid(P_i) = b_i P_{gi} + c_i \tag{3}$$

$$lbid(P_j) = \beta_j . C . P_j \tag{4}$$

The two policies formulated for the market operator are given as objectives in equations (5) and (6).

$$Minimize \quad Exp(P) \tag{5}$$

$$Maximize \;\; Profit(P) = [Rev(P) - Exp(P)] \tag{6}$$

Subject to constraints

$P_{gi}^{(min)} \leq P_{gi} \leq P_{gi}^{(max)}$; Generation limits (7)

$V_i^{(min)} \leq V_i \leq V_i^{(max)}$; Voltage limits for i^{th} node (8)

$-P_{grid}^{(max)} \leq P_{grid} \leq P_{grid}^{(max)}$; Grid power purchase/sell limits (9)

$\left[\sum_{i=1}^{m+n} P_{gi} + P_{grid} - P_d - P_{loss} + \sum_{j=1}^{l} P_j\right] \leq$ tolerance; Active power balance (10)

$0 \leq P_j \leq P_j^{(max)}$; Load curtailment limit (11)

Tolerance value is taken as 0.0001p.u (100kVA and 0.4kV base).With the profit maximization policy, the objective in equation (6) enforces revenue to a high value by selling more power to the upstream grid.

3. Methodology

3.1. Interval Arithmetic (IA)

The basic interval arithmetic operations [14] of two interval numbers X=[x_1, x_2] and Y=[y_1, y_2] are given as:

$$X + Y = [x_1 + y_1, x_2 + y_2] \tag{12}$$

$$X - Y = [x_1 - y_1, x_2 - y_2] \tag{13}$$

$$X \times Y = [min\,(x_1 \times y_1, x_1 \times y_2, x_2 \times y_1, x_2 \times y_2), max\,(x_1 \times y_1, x_1 \times y_2, x_2 \times y_1, x_2 \times y_2)] \tag{14}$$

$$X \div Y = X * Y^{-1}\ where\ Y^{-1} = \ [1/y_2, 1/y_1]\ if\ 0\ \notin\ [y_1, y_2] \tag{15}$$

However, for evaluation of power flow analysis, the above operations are modified for complex numbers Z_1=A_1+iB_1 and Z_2=A_2+iB_2 where A_1, A_2, B_1 and B_2 are interval numbers [15].

$$Z_1 +\ Z_2 = (A_1 + A_2) + i(B_1 + B_2) \tag{16}$$

$$Z_1 -\ Z_2 = (A_1 - A_2) + i(B_1 - B_2) \tag{17}$$

$$Z_1 \times\ Z_2 = (A_1 \times A_2 - B_1 \times B_2) + i(A_1 \times B_2 + A_2 \times B_1) \tag{18}$$

$$Z_1 \div\ Z_2 = C + iD \tag{19}$$

$$\text{where, } \mathrm{C} = (\mathrm{A}_1 \times \mathrm{A}_2 + \mathrm{B}_1 \times \mathrm{B}_2) \div (\mathrm{A}_2^2 + \mathrm{B}_2^2) \text{ and } \mathrm{D} = (\mathrm{A}_1 \times \mathrm{B}_1 - \mathrm{A}_1 \times \mathrm{B}_2) \div (\mathrm{A}_2^2 + \mathrm{B}_2^2) \tag{20}$$

It is to be noted that equations (12)-(15) have to be used for evaluating equations (16)-(20).

3.2 IA-BFS and PSO-TVAC Based OPF

The uncertain input data of the optimal power dispatch algorithm is handled by interval arithmetic and strong bounds are provided for the solution variables. All possible solutions corresponding to the uncertainties in the input variables are included in these bounds. The active power injections from the nodes to which the uncertain sources or loads are connected, can be represented as intervals in the IA based power flow [14]. Here, wind & solar generation and loads are the sources of uncertainties from which interval power injections are expected. Some sample representations of wind, solar and load demand intervalsare shown below. The intervals of wind, solar and demand are given in equation (21). The definition of upper and lower limits of intervals are given in equations (22)-(25).

$$P_{gw} \ = (\underline{P}_{gw}, \overline{P}_{gw}), P_{gs} \ = (\underline{P}_{gs}, \overline{P}_{gs}), P_d \ = \ (\underline{P}_d, \overline{P}_d) \tag{21}$$

$$\overline{P}_{gw} = P_{gw0} + \ \varepsilon_{w,pos} \tag{22}$$

$$\underline{P}_{gw} = P_{gw0}\ \text{-}\ \varepsilon_{w,neg} \tag{23}$$

$$\overline{P}_{gs} \ = \ P_{gs0} \ + \ \varepsilon_{s,pos} \tag{24}$$

$$\underline{P}_{gs} = P_{gs0}\text{-}\varepsilon_{s,neg} \tag{25}$$

Central values of intervals are found from equations (26), (27) and (28)

$$P_{gw0} = \frac{\underline{P}_{gw} + \overline{P}_{gw}}{2} \tag{26}$$

$$P_{gs0} = \frac{\underline{P}_{gs} + \overline{P}_{gs}}{2} \tag{27}$$

$$P_{d0} = \frac{\underline{P}_d + \overline{P}_d}{2} \tag{28}$$

Active power intervals of these uncertain sources are taken as input and the remaining power flow variables are found in the form of similar intervals, from backward forward sweep. Substituting the dispatch intervals in the objective functions (6) and (7), cost and profit intervals are obtained. The uncertainties in wind, solar and load depend on the forecast time frame. Here,40% (ε_w),20% (ε_s)and 3%(ε_d)uncertainties are considered for active power injections(kW) of wind, solar and load respectively, in hour ahead forecasting [16] [17].The solution of OPF will be also in the form of intervals in which one bound corresponds to negative uncertainty and the other corresponds to positive uncertainty.

PSO is a population based evolutionary computation technique inspired from the social behavior of bird flocking. In PSO-TVAC [4], the velocity and position of the particles are updated iteratively using equations (29) and (30) to find best position, p_{best} and the overall best position g_{best}.

$$v_{i,d}{}^{ic+1} = \omega^{ic} \times v_{i,d}{}^{ic} + a_1{}^{ic} \times rand_1\left(p_{best}{}^{ic} - x_{i,d}{}^{ic}\right) + a_2{}^{ic} \times rand_2(g_{best}{}^{ic} - x_{i,d}{}^{ic}) \quad (29)$$

$$x_{i,d}{}^{ic+1} = x_{i,d}{}^{ic} + v_{i,d}{}^{ic} \quad (30)$$

Where,

$$\omega^{ic} = [\omega^{max} - [\{\frac{\omega^{max} - \omega^{min}}{ic_{max}}\} \times ic] \quad (31)$$

$$a_i^{ic} = [a_i^{max} - [\{\frac{a_i^{max} - a_i^{min}}{ic_{max}}\} \times ic]\ ; \quad i = 1, 2 \quad (32)$$

The methodology for optimizing microgrid market benefits, combining PSO-TVAC and IA-BFS is presented below. The standard node voltage and line current representations are in line with Fig. 1.

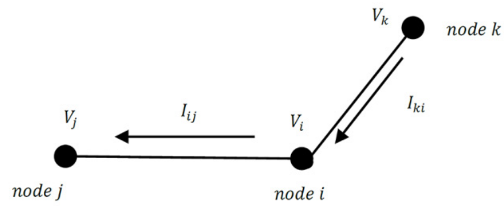

Fig.1. Node voltage and line current representations

Step 1:Initialize np particles in the interval form for the selected nc control variables within the limit. Set maximum iteration count = ic_{max}.

Step 2: Set power flow iteration count, ic=1. Set all nodes except the grid connected node as PQ. Set grid connected node as slack. Also set an initial voltage interval of[1+j0, 1+j0] for all the nodes.

Step 3: Set $ic = ic + 1$ and execute backward sweep to find line current interval, $I_{ij} = I_{ki} + \frac{P_i - jQ_i}{V_i{}^*}$

Step 4:Execute forward sweep to find voltage interval at j^{th} node connected to i^{th} node, $V_i - I_{ij} Z_{ij} = V_j$.

Step 5: If $V_j \geq V_j^{(max)}$ forentire voltage interval, then $V_j = V_j^{(max)}$ and update $Q_j$else$V_j = V_j^{(min)}$and updateQ_j.

Step 6: If voltage intervals $V^{ic} = V^{ic-1}$ for all nodes, then calculate the line flow interval, $S_{ij} = (V_i \angle \delta_i) \times [\frac{(V_i \angle \delta_i) - (V_j \angle \delta_j)}{Z}]^*$ and line loss interval $S_{ij(loss)} = I_{ij}{}^2 Z$else go to Step 3.

Step 7: Evaluate the fitness function to find the intervals of p_{best} and g_{best}

Step 8: If itr>ic_{max} , then go to Step 9. Else find the new velocity and position of the particles using equations (29) and (30), Set V^{ic}= 1and ic = 1 and go to Step 3.

Step 9: Output the intervals of fuel & emission costs, revenue, expense, profit, and power flow variables.

4. Test System

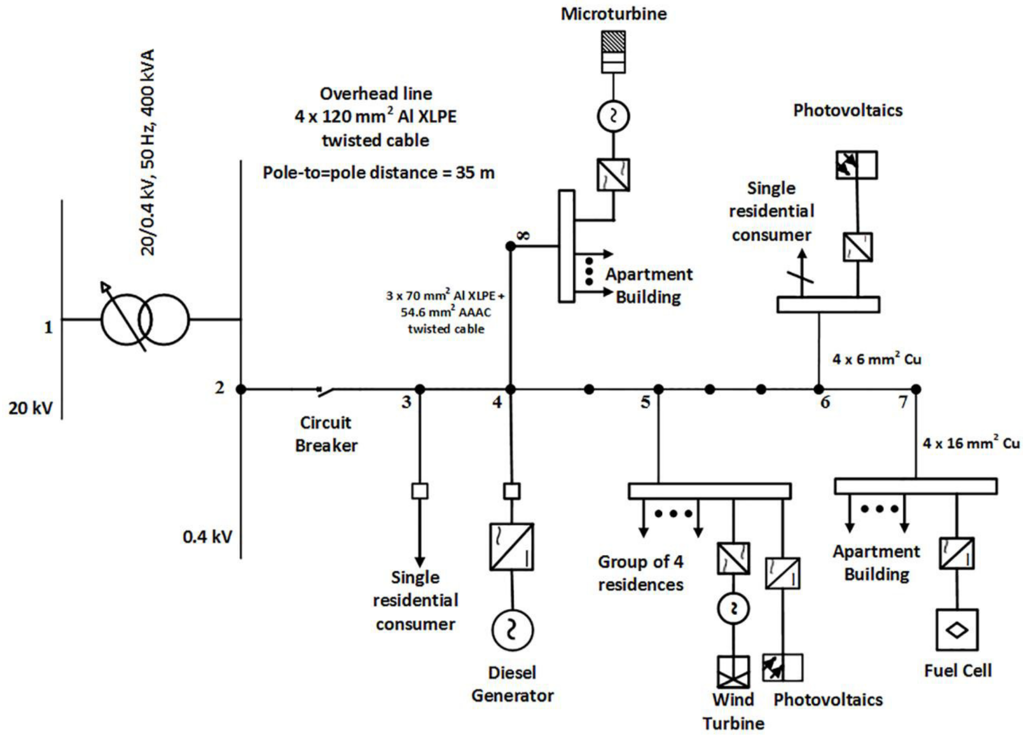

Fig. 2 Residential feeder of CIGRE LV benchmark

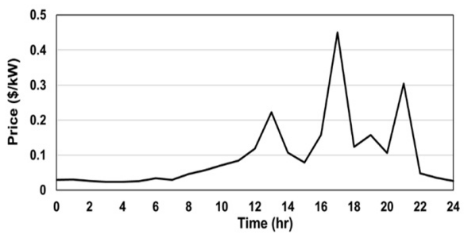

Fig. 3. Grid power price

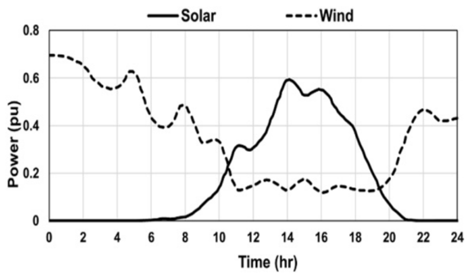

Fig. 4. 24hrs forecast of wind and solar power generation

The test system is shown in Fig 2. The models of fuel cell, microturbine and diesel generator and their cost functions are given in [2].TheSolar PV source is considered as PQ node in power flow, which injects active and reactive power into the microgrid. Nodal power factor is assumed to be 0.9 and voltage range is from 0.95p.u to 1.05p.u. Grid power price is shown in Fig. 3. Grid trade is limited to one third of the maximum demand to avoid overdraw of power during off-peak hours in which open market price is lower than the DER bids. A 10kW wind generator is connected at 5^{th} node of the feeder. 24hrs forecasted generation of solar and wind are shown in Fig. 4.The curtailable loads1 and 2 (CL1 AND CL2) at nodes 3 and 7 are curtailable by a maximum of 50%. $\beta$for CL1 and CL2 are assumed to be 1.5 and 0.8, i.e. CL1 is costlier to curtail when compared to CL2 based on the criticality.

5. Results and Discussions

The parameter settings of PSO-TVAC for optimal results are $\omega^{max} = 0.9$, $\omega^{min} = 0.4, a_1^{max} = 0.4, a_2^{max} = 2$, $a_1^{min} = 2, a_2^{min} = 0.4$, $ic_{max} = 300\ and\ np = 40$. Fig. 5 shows the 24 hrs forecasted demand from which the perturbations are considered. Table 1 shows the comparison of results of deterministic power scheduling (corresponding to forecasted values of renewable energy and demand) with that of stochastic scheduling

Table 1. Comparison of deterministic and stochastic power scheduling

Policy adopted by MGCC	Conventional DER gen (kW)	Net grid power (kW)	Load Curtailed (kW) CL1	Load Curtailed (kW) CL2	Fuel cost ($)	Emission cost ($)	Expense ($)	Profit ($)
Deterministic Scheduling (without considering uncertainties)								
1. Min cost policy	1249.66	151.42	11.46	75.28	87.79	15.58	134.44	47.2
2. Max profit policy	1576.09	-137.18	3.5	46.90	95.8	23.53	125.52	112.58
Stochastic Scheduling (corresponding to $\pm 40\%$, $\pm 20\%$ and $\pm 3\%$ uncertainties in wind, solar and load respectively)								
1. Min cost policy	[1075.41, 1253.91]	[142.80, 208.78]	[7.55, 27.04]	[65.68, 99.92]	[80.28, 90.24]	[14.27, 15.84]	[125.92, 147.83]	[46.16, 48.42]
2. Max profit policy	[1484.60, 1698.35]	[-90.37, -220.39]	[3.22, 4.01]	[27.68, 72.11]	[89.48, 104.44]	19.24, 26.70]	[119.5, 150.98]	[87.03, 114.92]

(considering uncertainties in renewable energy output and demand).Without considering uncertainties, the total profit for policy-1 is 47.2$ whereas policy-2 gives a better profit of 112.58$ because of the enforcement of high revenue in equation (6). This makes the net grid power (purchased power− sold power) negative in policy-2. CL1 is curtailed very less when compared to CL2 in both the policies because of its high bid. But, total curtailment (CL1+CL2) is high for policy-1 because of the enforcement of low fuel and emission costs (in DER bids) and thus a lower generation from conventional sources (1249.66<1576.09).Considering -40%, -20% and +3% uncertainties in wind, solar and load respectively, the profit dips in to 87.03$ for policy-2 and 46.16$ for policy-1. This is because of the extra kilowatts generated from the conventional sources, curtailment and grid purchase to counteract the deficit scenario. This extra power can be taken from spinning reserve for compensating the uncertainties in renewable energy and load. If this reserve is purchased from a separate reserve market, the bids may be more expensive (even though, separate bids for energy and reserve markets are not considered in this paper) and the profit can further be dipped in a realistic scenario. Similarly, profit (48.42$ and 114.92$ for policies 1 & 2 respectively) is better for both the policies in the excess scenario (+40%, +20% and -3%). However, policy-2 is more sensitive (a dip of around 25$ in profit for deficit scenario) to the unpredictability of renewable energy and demand. The difference in reserve requirements for the two policies in the deficit scenario are shown in Fig. 6.The reserve requirement is maximum at the 13th hr for both the policies because of the highest renewable energy generation (wind + solar) at that hour (See

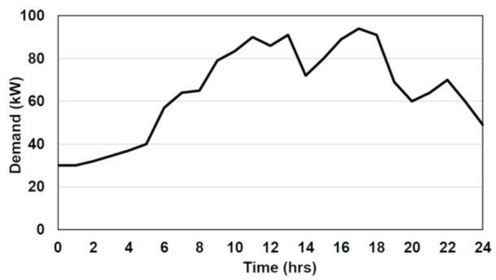

Fig. 5. Demand curve for 24 hours

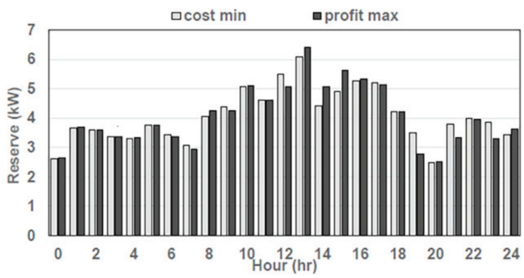

Fig. 6. Reserve for both policy

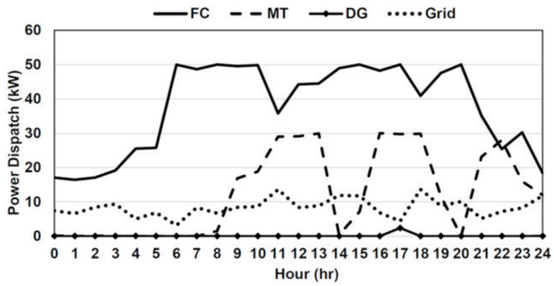

Fig. 7. Power Dispatch in Policy 1- Cost minimization

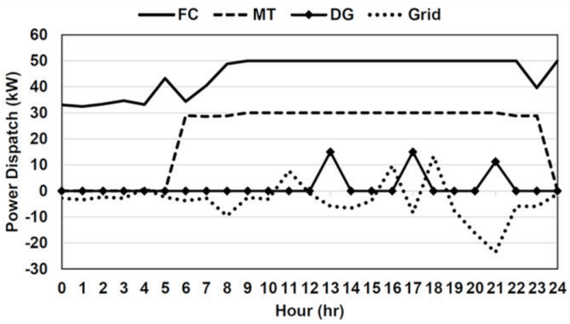

Fig. 8. Power Dispatch in Policy 2- Profit Maximization

Fig. 4). Fig. 7 & Fig. 8 depict the power dispatches from the conventional sources and the grid including the reserve for compensating the uncertainties. The dynamic response of the sources are better in policy – 2 since lesser fluctuations are shown in Fig. 8. In contrast to policy-1, policy-2 uses the costliest diesel generator is used in the three grid price peaks at hours 13, 17 and 21 since emphasis is given to generate more power from the local sources and to sell it to the grid. Thus, the grid power is negative in almost all hours for policy-2 (See Fig. 8) whereas it is positive for policy-1(See Fig. 7).

6. Conclusion

The stochastic effects of renewable energy and loads on optimizing microgrid market benefits are studied in this paper. IA-BFS and PSO-TVAC based OPF was implemented in the CIGRE LV benchmark microgrid, comparing two different policies of the MGCC in terms of cost, profit and power dispatch. Profit maximization policy performed better in terms of dynamic response of sources and earned better profits whereas cost minimization policy was lesser sensitive to uncertainties. In general, if the possible uncertainties in the market benefits are known prior to the actual dispatch, it is easier to plan the real time reserve and control requirements.

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